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Measurement of the Total-factor Energy Efficiency (TFEE) of China's Transportation Industry and Its Convergence in Consideration of Carbon Emissions

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Abstract

Traditional measures to control environmental pollution in the transportation industry mostly aim to limit carbon emissions and optimize the energy structure while ignoring the improvement in total-factor energy efficiency (TFEE). Effectively alleviating environmental pressure and promoting the high-quality development of the transportation industry within the agreed time range of carbon peak and carbon neutrality are difficult. To effectively address the issues of incomplete measurement indicators for single-factor energy efficiency and ignorance of the temporal association of carbon emissions, this study established an input–output indicator system for the TFEE of China's transportation industry, which was adopted as the investigation object, in consideration of carbon emissions. The TFEE of China's transportation industry was measured using the Malmquist–Luenberger index method in consideration of carbon emissions during 2004–2020. Then, the convergence or dispersion of TFEE was analyzed through a convergence model. Results revealed that with carbon emissions considered, the TFEE of China's transportation industry is 0.959 and presents an east–west–center gradually declining trend. The values of pure technical efficiency, scale efficiency, and technological changes are 1.026, 1.013, and 0.951, respectively. The provincial TFEE differences of the transportation industry have been existing for a long time, but the regions with low energy efficiency are catching up with those with high energy efficiency. The study's results are valuable for promoting China's transportation industry, reducing carbon emissions, conserving resources, and boosting the collaborative development of environmental protection and economic growth.

Keywords: transportation industry; total-factor energy efficiency; malmquist–luenberger index method; fossil energy; convergence model

Introduction

The rapid development of the transportation industry, an energy-intensive industry, is one of the important reasons for the ever-increasing energy consumption in China. The total-factor energy efficiency (TFEE) of the transportation industry must be accurately evaluated and improved to alleviate environmental pollution and realize energy conservation and emission reduction [1]. The energy consumption and carbon emission intensities of China's transportation industry are high and show an obvious increasing trend, making the task of energy saving and emission reduction in the transportation industry arduous and urgent [2]. Traditional methods of solving high carbon emissions within the transportation industry aim to reduce the total carbon emission and regulate the energy structure of this industry, but carbon emissions cannot be reduced within a short term because of the current sustainable development status and the relatively stable energy structure of China's transportation industry. Hence, correctly measuring the TFEE of the transportation industry and analyzing its convergence are important for quantitatively analyzing the influencing direction and the degree of its influencing factors [3]. Accurate TFEE measurements can be employed as a basis to formulate pertinent industrial policies in accordance with the importance of influencing factors, promote the transformation and upgrading of the transportation industry, and improve TFEE [4].

Data envelopment analysis (DEA), logarithmic mean divisia index, value at risk, and other methods have been widely applied to measure the TFEE of the transportation industry efficiently, and index system establishment, measurement of energy input diversity, and measurement of energy indicators have become research hotspots [5–8]. However, extant studies have focused on single-factor energy efficiency, and among all output indicators, only economic benefit has been considered. Energy efficiency is generally defined as a physical heat indicator in many documents, but this definition fails to reflect the relationship between traffic input and output. As a result, research on the convergence of energy efficiency is lacking, the temporal association of carbon emissions has been disregarded, and eco-environmental pollution and carbon emissions induced by the transportation industry have not been effectively identified. Hence, measuring the TFEE of the transportation industry through scientific evaluation methods, starting from the sole consideration of beneficial outputs to the comprehensive evaluation of unexpected outputs, is crucial for enriching such studies.

This study aims to scientifically evaluate the TFEE of the transportation industry in various regions of China, explore the key factors for TFEE improvement, and determine if the dispersion of TFEE will gradually decline with time. In this work, the TFEE of the transportation industry was scientifically measured through the Malmquist–Luenberger index method. The divergence of three convergence models for energy efficiency was studied in a combined manner to solve the problems of inaccurate measurement of single-factor energy efficiency and failure to identify the time lag of energy efficiency. This study scientifically identified the regional differences in TFEE of China's transportation industry and TFEE's temporal association.

State of the art

The carbon emission of the transportation industry was measured using top–down models in some studies. For instance, Sajia (2012) estimated the carbon emission of road transportation in similar regions of Italy through the top–down method and calculated the carbon emission induced by transportation on first-class roads [9]. Wang H. (2011) and Wang T. (2012) scientifically measured the carbon emission of China's transportation industry from two aspects: passenger transport and freight transport [10,11]. Meanwhile, Zhang (2019) consolidated the literature on the measurement of carbon emissions in China's transportation industry and interpreted top–down models in detail [12]. Unlike the top–down pattern, the bottom–up pattern needs to acquire the original microscopic behavior data of transportation subjects; such data encompass the category, quantity, and travel distance of means of delivery under various modes of transportation. Then, the total energy consumption of transportation is converted, and the carbon emission of the transportation industry is calculated. Mensink (2000) proposed a detailed modeling method and calculated the carbon emission of the transportation industry on the basis of statistical data, such as road type, vehicle type, fuel type, traffic volume, vehicle age, travel length distribution, and actual environmental temperature [13]. Lin (2010; five parks in Taiwan Province, China) [14], Ramachandra (2009; road transportation in each state of India) [15], and Timilsina (2010; 20 Latin

American countries) [16] measured the carbon emissions of transportation industries.

To assess the TFEE of the transportation industry, Zhang (2015) analyzed the total-factor carbon emission performance of China's transportation industry by using the nonradial Malmquist index [17]. Zhou (2014) proposed a multidirectional-efficiency nonradial DEA model with unexpected output to measure the regional TFEE and environmental efficiency of China's transportation industry from 2006 to 2010 [18]. Liu (2018) studied the interprovincial TFEE of China's transportation industry and its influencing factors. The results showed that interprovincial TFEE has a ladder-like distribution, and the interprovincial TFEE gap is gradually narrowing [19]. Feng (2018) assessed the overall efficiency of the land transport sector in China and found that the performance of railway transport is better than that of road transport; the author also reported that the TFEE of China's transportation industry has declined mainly because of the decrease in management efficiency and the widening regional technology gap [20]. Xie (2018) posited that the national average energy input efficiency of China's transportation industry is 0.673, indicating high inefficiency [21]. Compared with Chinese scholars, scholars in developed countries tend to calculate carbon emission efficiency more scientifically and accurately for a specific industry or region in the transportation industry. Llorca (2017) analyzed the TFEE and rebound effect of road freight transportation in 15 European countries from 1992 to 2012. The results showed that the obtained TFEE has been largely retained [22]. Zhou et al. (2010) studied the emission performance of 18 CO2-emitting countries in the world during 1997–2004. They discovered that during this period, the total-factor carbon emission performance of all the countries improved by 24% mainly because of technological progress [23]. Ramanathan (2005) performed a scenario analysis to determine the effect of some mode splits that are beneficial to railway transportation on future energy consumption and CO2 emissions. The research showed that railway transport accounted for 50% of the total transportation modes during 2005–2006 and 2020–2021 [24]. Greening et al. (1999) analyzed the freight industry in 10 OECD countries and found that the increase in total carbon intensity in 9 of them ranges from less than 20% to more than 150% possibly because the change in mode structure to the carbon-intensive mode [25]. Chang et al. (2014) calculated the carbon emission efficiency of 27 airlines around the world. The results showed that Asian airlines are highly efficient, followed by European and American airlines [26]. Li et al. (2016) calculated the TFEE of 22 airlines, and the results revealed that the TFEE of these airlines is low [27]. Liimatainen et al. (2010) studied the TFEE of road freight in Finland and found that the TFEE of road freight in Finland improved during 1995–2002 but decreased after this period [28]. Cui et al. (2014) presented a three-stage, virtual-boundary DEA method and used 30 provincial administrative regions in China from 2003 to 2012 as examples to verify the method's rationality [29]. Li (2022) reported that the inhibitory effect of TFEE on the carbon emissions of China's transportation industry is enhanced with the improvement of TFEE [30]. Lv (2023) concluded that the visualization of traffic data in the management system plays a crucial role in alleviating traffic congestion and reducing traffic energy consumption [31].

Previous studies thought that the total energy consumption of the transportation industry in developing countries (represented by China) is high. Despite efforts to improve TFEE, the TFEE of the transportation industry in many developing countries improves slowly because of the gaps in infrastructure construction, vehicle technology update, traffic management level, and public awareness of energy conservation. By implementing strict energy efficiency standards and carbon emission-related laws and regulations, the governments of some developing countries have promoted the extensive application of efficient and energy-saving vehicles and clean energy sources, such as electric, hybrid electric, and hydrogen vehicles, which have considerably reduced the carbon emission and energy consumption of the transportation industry. The development of the intelligent transportation system, including traffic flow management, vehicle navigation system, and public transport optimization, has also effectively improved the operating efficiency of transportation networks and reduced energy wastage. In addition, the energy structure and policy orientation of different countries have markedly influenced the energy consumption and efficiency of the transportation industry.

Here, an empirical study was performed based on the panel data of the input and output indicators of the transportation industry in 30 provinces of China during 2004–2020 to address the deficiency of existing research. Specifically, the TFEE of China's transportation industry was measured through the Malmquist–Luenberger index method, and the convergence of the TFEE of China's transportation industry in consideration of carbon emissions was analyzed through three convergence models. Moreover, the divergence or convergence of the TFEE of China's transportation industry over time was explored. In this way, interregional differences can be identified, and measures can be implemented to promote balanced development and further reduce the carbon emission of the transportation industry.

The remainder of this paper is organized as follows. In Section III, the Malmquist–Luenberger index method and the convergence method are briefly introduced. In Section IV, the TFEE of the transportation industry is measured through the Malmquist–Luenberger index method. Then, TFEE is decomposed into a pure efficiency change index and a scale efficiency change index, and three convergence models are used to analyze the divergence trend of the TFEE of the transportation industry in detail. In Section V, the results of this study are summarized, and relevant conclusions are presented.

Methodology

Malmquist–Luenberger index method

A potential production set that includes expected and unexpected outputs should be established before calculating the TFEE of China's transportation industry. In this study, the transportation industry in each province (autonomous regions and municipalities directly under the central government) of China was adopted as a decision-making unit. Each decision-making unit was assumed to have production input factors expressed as $x=(x_1,\cdots,x_n)\in R_+^N$, expected output factors expressed as $y=(y_1,\cdots,y_m)\in R_+^M$, and I unexpected output factors expressed as $b=(b_1,\cdots,b_I)\in R_+^I$. Then, the production set was defined as a bounded closed set and expressed as

$$P(x)=\{(y,b): x\ can\ product(y,b)\}, x\in R_+^N \quad (1)$$

Chung et al. (1997) concluded that the unexpected output can be reduced by introducing a distance function [32], which aims to elevate the expected output by reducing the unexpected output on the basis of a directional distance function. A distance function can be expressed as

$$\vec{D}_0(x^t,y^t,b^t;g^t)=\sup\{\beta:(y^t,b^t)+\beta g^t\in p^t(x)\} \quad (2)$$

where g is the direction vector. When $g=(g_y,-g_b)$, the unexpected output can be reduced by improving the expected output. The directional distance function is then expressed as

$$\vec{D}_0(x,y,b;g_y,-g_b)=\sup\{\beta:(y+\beta g_y,b-\beta g_b)\in p(x)\} \quad (3)$$

where β stands for the distance function value used to describe the change in the output level. When $g=(g_y,-g_b)$, the production frontier is reached, the expected output increases while the expected output declines, and both achieve the optimal state. The directional distance function can be converted into a linear programming form as follows:

$$\max \vec{\beta} = D_0^t(x_{k'}^t, y_{k'}^t, b_{k'}^t; y_{k'}^t, -b_{k'}^t)$$

$$s.t.\begin{cases} \sum_{k=1}^{K} z_k^t y_{km}^t \geq (1+\beta) y_{k'm}^t, m = 1, \cdots, M \\ \sum_{k=1}^{K} z_k^t b_{ki}^t = (1-\beta) b_{ki}^t, i = 1, \cdots, I \\ \sum_{k=1}^{K} z_k^t x_{kn}^t \leq x_{k'n}^t, n = 1, \cdots, N \\ z_k^t \geq 0, k = 1, \cdots, K \end{cases} \quad (4)$$

where z_k^t represents the intensity variable and $\beta = 0$ means that the production remains at the frontier. The greater the value of β is, the lower the production efficiency of decision-making units is. The Malmquist–Luenberger index method needs to define the directional distance function of two adjacent periods, which can be expressed as

$$\vec{D}_0^{t+1}(x^t, y^t, b^t; g) = \sup\{\beta : (y^t, b^t)\} + \beta g \in p^{t+1}(x^t)\} \quad (5)$$

On the basis of the calculation method of Chung et al. (1997), the Malmquist–Luenberger productivity index can be expressed as

$$ML_t^{t+1} = \sqrt{\frac{1+\vec{D}_0^{t+1}(x^t, y^t, b^t, y^t, -b^t)}{1+\vec{D}_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})} \times \frac{1+\vec{D}_0^{t}(x^t, y^t, b^t; y^t, -b^t)}{1+\vec{D}_0^{t}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})}} \quad (6)$$

Färe et al. (2007) presented the decomposition method of the Malmquist–Luenberger index [33]. Under constant returns to scale, the index can be decomposed into technical efficiency (EC) and technological progress (TC) indices; the former reflects the chasing effect toward the boundary of the production frontier from period t to period $t+1$, and the latter reflects the intertemporal movement from period t to period $t+1$. The decomposition method is given as

$$EC = \frac{1+\vec{D}_0^{t}\left(x^t, y^t, b^t; y^t, -b^t\right)}{1+\vec{D}_0^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)} \quad (7)$$

$$TC = \sqrt{\frac{1+\vec{D}_0^{t+1}\left(x^t, y^t, b^t; y^t, -b^t\right)}{1+\vec{D}_0^{t}\left(x^t, y^t, b^t; y^t, -b^t\right)} \times \frac{1+\vec{D}_0^{t+1}\left(x^t, y^t, b^t; y^t, -b^t\right)}{1+\vec{D}_0^{t}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)}} \quad (8)$$

$EC = 1$ and $EC = 1$ indicate that EC and TC have no contributions to TFEE growth. $EC > 1$ and $TC > 1$ mean that EC and TC contribute to TFEE growth. $EC < 1$ and $TC < 1$ indicate that the growth of TFEE is impeded by the decline in EC and TC. Under constant returns to scale, in accordance with the decomposition method proposed by Färe et al. (1992), the EC index can be further decomposed into a pure efficiency change (PEC) index and a scale efficiency change (SEC) index.

Convergence model

The convergence of σ mainly aims to determine if the dispersion degree of TFEE of the transportation industry in three regions of China will gradually decline with time. In this study, the calculation formula proposed by Adhikari et al. (2014) [34] for the convergence of σ was adopted. The formula is given as

$$\sigma_t = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[TFP_i(t) - (\frac{1}{N}\sum_{k=1}^{N} TFP_k(t))\right]^2} \quad (9)$$

$TFP_i(t)$ represents the TFEE of the transportation industry in Province i (autonomous regions and municipalities directly under the central government) in period t. If σ_t exhibits a gradual decline over time, the convergence phenomenon of σ_t will appear. σ can be calculated through the linear regression method to measure the convergence of σ accurately.

$$y_t = \alpha + \beta t + \varepsilon \quad (10)$$

where y_t is the convergence value of σ, α is a constant term, β denotes the regression coefficient, t is the temporal trend, and ε is the random error term. When $\beta > 0$ and is significant, σ has a divergent trend; if $\beta < 0$ and is significant, σ exhibits convergence.

The absolute convergence of β aims to assess the correlation between the growth rate of TFEE of the transportation industry and its initial level. Given that the absolute convergence of β is a necessary but insufficient condition for the convergence of σ, the absolute convergence test of β should be performed after the convergence test of σ. In this study, measurement was performed using the formula of Bernard et al. (1996) [35] as follows:

$$\ln\left(y_{i,t+1}/y_{i,t}\right)/T = \alpha + \beta \ln y_{i,t} + \varepsilon_{it} \tag{11}$$

where $y_{i,t}$ represents the TFEE of the transportation industry in Province i (autonomous regions and municipalities directly under the central government) in period t, T is the length of the investigated period, α is a constant term, β is the regression coefficient, and ε_{it} is the random error term. If the regression result shows that $\beta > 0$ and the regression coefficient is significant, absolute β exhibits a divergent trend. If $\beta < 0$ as manifested by the regression result and the regression coefficient is significant, absolute β presents a convergent trend, which means that the speed of the increment in TFEE is reversely proportional to the initial level and that low-efficiency regions tend to catch up with high-efficiency ones.

Unlike absolute convergence, conditional convergence considers whether the TFEE of the transportation industry in different regions is temporally steady. According to new economic growth theory, the status of economic development varies in different periods or in regions within the same period. Different convergence conclusions will be obtained if these basic conditions are controlled. In this study, the method proposed by Cho et al. (1996) [36] was adopted, and the control variable was added to absolute β convergence. Afterward, if the regression coefficient is still $\beta < 0$ and significant, conditional β convergence appears. Hence, five environmental variables (industrial structure, economic level, technological progress, opening degree, and population density) were incorporated into conditional β convergence as control variables, and a panel data regression model was established, as shown in the equation

$$\ln(y_{i,t+1}/y_{i,t})/T = \alpha + \beta \ln y_{i,t} + \eta_1 str + \eta_2 eco + \eta_3 tec + \eta_4 ope + \eta_5 pop + + \varepsilon_{it} \tag{12}$$

where str represents the industrial structure, eco is the economic level, tec stands for technological progress, ope is the opening degree, pop denotes the population density, and $\eta(\mathrm{i} = 1, 2, \cdots, 5)$ represents the regression coefficients of the five control variables.

Index system establishment and data sources

According to classical economic growth theory, many inputs are required to drive the development of the transportation industry. Typical inputs include capital and labor force. In this study, which considered massive carbon emissions in the transportation industry, energy consumption was included as an input. Industrial value added is generally considered an output indicator. Meanwhile, given that the transportation industry is a typical derivative industry and facilitates the development of other industries, driving passenger and freight transport, comprehensive turnover volume was also employed as an output indicator. Given the high carbon emission in the transportation industry, such carbon emission was used as the unexpected output. The specific input–output indicators are listed in Table 1. All data were derived from the regional energy balance sheets of each province in China Energy Statistical Yearbook during 2005–2021.

Table 1. TFEE input, output, and unexpected output indicators of the transportation industry

Variable type	Variable name	Specific indicator
Input variable	Number of employees in the transportation industry	Employees in urban units in the transportation industry (10,000 persons)
	Fixed investments in the transportation industry	Capital stock of the transportation industry (RMB 100 million)
	Energy consumption of the transportation industry	Energy consumption of the transportation industry (million tons of standard coal)
Output variable	Value added in the transportation industry	Value added in the transportation industry (RMB 100 million)
	Comprehensive turnover volume of the transportation industry	Passenger and freight turnover volume of the transportation industry (100 million tons per kilometer)
Unexpected output variable	Carbon emission in the transportation industry	Carbon emission in the transportation industry (1 million tons)

Result analysis and discussion

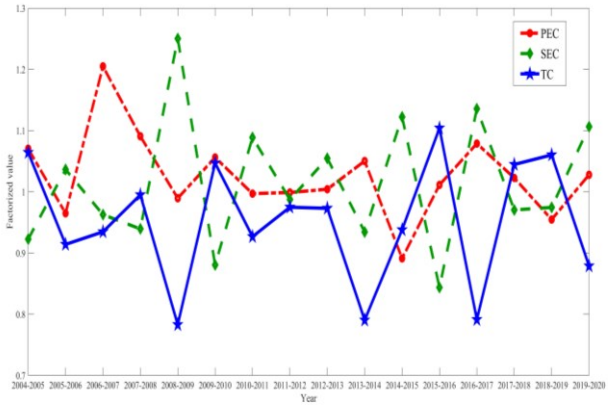
Calculation of TFEE of the transportation industry

Table 2. TFEE of China's transportation industry

Province	TFEE	Province	TFEE	Province	TFEE
Beijing	0.919	Shanxi	0.954	Inner Mongolia	0.937
Tianjin	1.036	Jilin	0.917	Guangxi	0.936
Hebei	0.958	Heilongjiang	0.967	Chongqing	0.928
Liaoning	0.964	Anhui	0.891	Sichuan	0.940
Shanghai	1.091	Jiangxi	0.954	Guizhou	0.948
Jiangsu	0.940	Henan	0.887	Yunnan	0.997
Zhejiang	1.121	Hubei	0.969	Shaanxi	1.008
Fujian	0.901	Hunan	0.945	Gansu	0.952
Shandong	0.966	Central region	0.935	Qinghai	0.952
Guangdong	0.981	-	-	Ningxia	0.930
Hainan	0.969	-	-	Xinjiang	0.967
Eastern region	0.986	-	-	Western Region	0.954
	Nationwide			0.959	

As shown in Table 2, the average TFEE of China's transportation industry from 2005 to 2020 was 0.959, which indicates that the production frontier is not completely reached and that no importance is attached to low consumption of resources and environmental protection during the long-term development process of China's transportation industry. The development of the transportation industry has excessively relied on capital and human resource input, placing specific pressure on environmental protection. On the whole, the TFEE of the transportation industry in Zhejiang, Shanghai, Tianjin, and Shaanxi is greater than 1, manifesting that the productivity of the four regions has substantially improved (the top four). Zhejiang and Shanghai are located in the Yangtze River Delta Economic Zone in China. Their overall transportation industry is developed, and their transportation planning is reasonable. Therefore, the TFEE of the transportation industry has considerably improved. Tianjin is located in the Beijing–Tianjin–Hebei region, which has good transportation infrastructure conditions and a high degree of intensive development. Among the provinces, Anhui and Henan had the lowest TFEE (both were less than 0.9), so they were ranked as the bottom two. The two provinces are populous, and agriculture and industries account for a relatively large proportion. In the two provinces, the transportation industry has not achieved intensive production while ensuring the speed of economic and social development, which has led to the low TFEE of the transportation industry. The TFEE of the transportation industry in the three major administrative regions of China showed an east–west–center decreasing order.

TFEE factor decomposition of the transportation industry



Figuer 1: TFEE factor decomposition of China's transportation industry

As shown in Figure 1, the TFEE of China's transportation industry during 2004–2020 could be decomposed into three aspects for interpretation.

1. PEC: During the investigation period, the average change in the PEC of China's transportation industry was 1.026, which was greater than 1. The PEC in 10 of the 16 time periods was greater than 1, with an average annual increase of 0.46%, indicating that the PEC level of China's transportation industry improved during the investigation period because of the improvement in the operation management level and organizational efficiency.

2. SEC: During the investigation period, the average change in the scale efficiency of China's transportation industry was 1.013, which was greater than 1. The SEC in 7 out of 16 time periods was greater than 1, with an average annual increase of 0.48%. This finding reveals that during the investigation period, China's transportation industry achieved scale efficiency growth by increasing infrastructure construction and improving the structure of employees engaged in the transportation industry.

3. TC: During the investigation period, the average TC of China's transportation industry was 0.951, which was less than 1. The TC in 11 of the 16 time periods was less than 1, with an average annual decrease of

0.27%. These results indicate that the low TFEE of China's transportation industry is mainly due to the inhibition of technological changes, and the transformation and upgrading of production facilities and equipment, the enhancement of the large-scale application of energy-saving and emission-reduction technologies in the transportation industry, and the promotion of clean energy use still need improvement.

Table 3. TFEE decomposition of transportation industries in eastern, central, and western regions

Province	PEC	SEC	TC
Beijing	1.021	1.011	0.914
Tianjin	0.996	1.004	1.041
Hebei	1.000	1.000	0.958
Liaoning	1.049	0.998	0.947
Shanghai	1.000	1.079	1.172
Jiangsu	1.039	1.014	0.923
Zhejiang	1.061	1.017	1.079
Fujian	0.987	1.001	0.910
Shandong	1.022	1.022	0.956
Guangdong	1.108	1.089	0.953
Hainan	1.024	1.040	0.937
Shanxi	1.066	1.016	0.902
Jilin	1.036	1.010	0.920
Heilongjiang	1.032	1.014	0.941
Anhui	0.980	0.994	0.920
Jiangxi	1.066	1.016	0.902
Henan	1.026	1.008	0.865
Hubei	1.046	1.004	0.929
Hunan	1.030	1.004	0.927
InnerMongolia	0.979	1.006	0.970
Guangxi	1.022	1.033	0.940
Chongqing	0.994	1.005	0.936
Sichuan	0.999	0.998	0.954
Guizhou	1.018	1.038	0.970
Yunnan	1.083	0.988	0.949
Shaanxi	1.065	1.010	0.949

Gansu	1.007	1.009	0.970
Qinghai	0.987	0.991	0.981
Ningxia	1.000	0.991	0.963
Xinjiang	1.006	1.002	0.970
Easternregion	1.028	1.025	0.981
Centralregion	1.035	1.008	0.914
Beijing	1.021	1.011	0.914
Tianjin	0.996	1.004	1.041

As shown in Table 3, the TFEE of China's transportation industry during 2004–2020 could be decomposed into three aspects for interpretation.

1. PEC: During the investigation period, the PEC values of 23 provinces (autonomous regions and municipalities directly under the central government) were all higher than 1, indicating that the transportation industry in most provinces (autonomous regions and municipalities directly under the central government) has grown rapidly because of improved management and operation levels. Among the provinces, Guangdong, Yunnan, and Shanxi ranked the top three in terms of PEC. Specifically, the PEC value in the central, eastern, and western regions was 1.035, 1.028, and 1.015, respectively. The PEC in the central region was higher than that in the two other regions.

2. (SEC: During the investigation period, the SEC values of 24 provinces (autonomous regions and municipalities directly under the central government) were all higher than 1, indicating that the vast majority of provinces (autonomous regions and municipalities directly under the central government) have continuously expanded the scale of the transportation industry, and the scale efficiency changes have increased because of the implementation of additional active guiding policies. Among the provinces, Guangdong, Shanghai, and Hainan ranked the top three provinces in terms of SEC. Specifically, the SEC value in the eastern, central, and western regions was 1.025, 1.008, and 1.006, respectively; the SEC value in the eastern region was higher than that in the other regions. The eastern region has a solid overall economic foundation and a high degree of development, accompanied with high economic strength, to promote the scale expansion of the transportation industry.

3. TC: During the investigation period, the TC values in only three provinces (autonomous regions and municipalities directly under the central government) were higher than 1, revealing that the transportation industry in most provinces (autonomous regions and municipalities directly under the central government) has not effectively achieved technological changes and growth, and TFEE is greatly affected by the decline in the technical level. Among the provinces, Shanghai, Zhejiang, and Tianjin ranked at the top in terms of TC. Specifically, the TC value in the eastern, western, and central regions was 0.981, 0.960, and 0.914, respectively, and the TC value in the eastern region was higher than that in the other regions. Given that the TC values of Shanghai, Zhejiang, and Tianjin are greater than 1, the other provinces (municipalities directly under the central government) in the eastern region have slowed down the technological change in the eastern region, making it necessary to strengthen the coordinated development of the transportation industry in different provinces (autonomous regions and

municipalities directly under the central government) in the eastern region. In addition, the TC value in the western region was higher than that in the central region. Owing to the implementation of the Belt and Road Initiative in recent years, many western provinces (autonomous regions and municipalities directly under the central government) have introduced high technology in the transportation field, which has improved the application level of emerging technologies in this industry.

TFEE convergence analysis of the transportation industry

Table 4. Convergence results

Year	Nationwide	Eastern region	Central region	Western region
2004–2005	0.345	0.417	0.155	0.217
2005–2006	0.192	0.180	0.121	0.207
2006–2007	0.166	0.113	0.058	0.219
2007–2008	0.086	0.067	0.134	0.051
2008–2009	0.260	0.309	0.271	0.143
2009–2010	0.263	0.309	0.228	0.188
2019–2011	0.138	0.197	0.099	0.081
2011–2012	0.102	0.127	0.109	0.060
2012–2013	0.134	0.110	0.149	0.102
2013–2014	0.260	0.314	0.324	0.114
2014–2015	0.262	0.300	0.277	0.103
2015–2016	0.263	0.340	0.222	0.082
2016–2017	0.176	0.269	0.106	0.061
2017–2018	0.173	0.217	0.070	0.070
2018–2019	0.215	0.268	0.151	0.143
2019–2020	0.157	0.180	0.131	0.092

Table 4 shows that the TFEE of China's transportation industry could be divided into four stages on the whole. The fourth evident convergence appeared in four time periods, namely, 2004–2008, 2009–2013, 2014–2018, and 2019–2020, but a fluctuating declining trend was manifested on the whole, without obvious σ convergence.

An absolute β convergence analysis was conducted. Before regression, the selection of a random or fixed effect for panel data was judged through the Hausman statistical test, the results of which are listed in Table 5.

Table 5. Hausman statistical test results

Area	Chi-Sq. Statistic	Prob.

Nationwide	16.622	0.000***
Eastern region	12.855	0.001***
Central region	3.109	0.078*
Western region	0.425	0.515

(Notes: *** denotes the significance level of 1%, and * indicates the significance level of 10%)

As shown in Table 5, the original Hausman assumption was rejected by the results for the whole country, eastern region, and central region; thus, a fixed-effect model should be adopted. In the western region, the original Hausman assumption was accepted, so a random-effect model should be used. The model decomposition results are given in Table 6.

Table 6. Absolute β convergence test results

Variable	Coefficient	Standard Deviation	T-value	P-value
		Nationwide		
α	−1.073	0.044	−24.579	0.000***
β	−0.138	0.018	−7.524	0.000***
		Eastern region		
α	−0.126	0.033	−3.840	0.002***
β	−1.138	0.079	−14.418	0.000***
		Central region		
α	−0.146	0.037	−3.898	0.002***
β	−0.983	0.089	−11.018	0.000***
		Western region		
α	−0.140	0.026	−5.340	0.000***
β	−1.061	0.061	−17.487	0.000***

(Notes: *** denotes the significance level of 1%)

As shown in Table 6, the absolute β convergence models for the TFEE of the transportation industry throughout China and in the eastern, central, and western regions achieved good estimation results. The coefficient regression result was always highly significant at the confidence interval of 1%, and the P value was smaller than 0.01. On the national scale, the TFEE of the transportation industry in each province (autonomous regions and municipalities directly under the central government) presented a convergent trend. The same marked convergence characteristics were manifested in the eastern, central, and western regions, and the convergent trend was the most evident in the western region. Similar to the measurement of absolute β convergence, the selection of a random or fixed effect for the panel data model was judged first, and the test was completed via Hausman statistics, as shown in Table 7.

Table 7. Hausman statistical test

Area	Chi-Sq. Statistic	Prob.
Nationwide	115.817	0.000***
Eastern region	19.425	0.004***
Central region	65.041	0.000***
Western region	302.478	0.000***

(Notes: *** denotes the significance level of 1%)

Table 7 indicates that the original Hausman assumption was rejected by the results for entire China and for eastern, central, and western regions, indicating that a fixed effect should be adopted for the four panel data regression models. The regression results are listed in Table 8.

Table 8. Conditional β convergence test results

Variable	Coefficient	Standard deviation	P value	Variable	Coefficient	Standard deviation	P value
	Nationwide				Centralregion		
β	−0.019	0.002	0.000***	β	−0.028	0.004	0.000***
α	0.058	0.037	0.112	α	0.149	0.067	0.027**
Industrialstructure	−0.008	0.007	0.249	Industrialstructure	−0.020	0.010	0.055*
Economiclevel	0.008	0.005	0.083*	Economiclevel	−0.023	0.011	0.040**
Technologicalprogress	−0.008	0.004	0.106	Technological progress	−0.010	0.009	0.267
Openingdegree	−0.002	0.004	0.665	Openingdegree	−0.008	0.008	0.348
Populationdensity	0.008	0.003	0.009***	Populationdensity	0.014	0.006	0.018**
	Easternregion				Westernregion		
β	−0.075	0.005	0.000***	β	−0.020	0.002	0.000***
α	−0.160	0.121	0.187	α	0.241	0.034	0.000**
Industrialstructure	0.029	0.017	0.089*	Industrialstructure	−0.028	0.011	0.013**
Economiclevel	0.024	0.015	0.049**	Economiclevel	−0.032	0.004	0.000**
Technologicalprogress	−0.012	0.010	0.227	Technological progress	0.007	0.002	0.003***
Openingdegree	0.030	0.016	0.053*	Openingdegree	0.006	0.004	0.115

Populationdensity	0.004	0.012	0.715	Populationdensity	0.001	0.003	0.805

(Notes: *** means the significance level of 1%, ** indicates the significance level of 5%, and * denotes the significance level of 10%)

As presented in Table 8, after the control variables were added to the absolute convergence model, the β value became negative throughout China and in the three major administrative regions, and it was significant at the level of 1%. Conditional β convergence existed in the TFEE of the transportation industry throughout China and in the three major regions, and the spatial differences gradually narrowed with the passage of time, with backward regions exhibiting the “chasing effect.” As revealed by the regression coefficient, the convergence speed in the eastern region contributed greatly to the TFEE convergence of the nationwide transportation industry. This finding indicates that the transportation industry in the eastern region can be easily affected by other policy factors, and the conditional β convergence trend in the eastern region is relatively steady.

With regard to industrial structure, which was among the control variables, the regression coefficient at the national level was negative but not significant, showing that the adjustment and upgrading of the industrial structure have failed to increase the TFEE convergence speed of China’s transportation industry. The regression coefficient in the eastern region was positive and significant at the level of 10%, manifesting that because of the relatively large proportion of the secondary industry in the eastern region, the TFEE of the transportation industry in this region converges rapidly. Given that the transportation industry belongs to a derivative industry, the secondary industry in the eastern region has vigorous production demands, which can evidently promote the collaborated improvement of production efficiency within the transportation industry in this region. However, for the central and western regions, the regression coefficient was negative and significant at the levels of 10% and 5%, respectively, indicating that the increase in the proportion of the secondary industry in the central and western regions has not accelerated the convergence of the TFEE of the transportation industry. Given that the transportation industry in the central and western regions is still in a period of rapid development, bulk cargo transportation in the primary and secondary industries must be completed to obtain a reasonable output, and additional consideration should be given to the actual production and service demand of the transportation industry in the central and western regions.

With regard to economic level, which was one of the control variables, the regression coefficients of the central and western regions were negative and significant at the level of 5%, indicating that the per capita GDP of the central and western regions has not sufficiently supported the improvement of the TFEE of the transportation industry. Given that the transportation industry needs sufficient economic support, the economic foundation of the central and western regions is weak, and the investments in transportation, scientific and technological innovation, and technological research and development (R&D) are not as good as those in the eastern regions. The economic aggregate needs to be continuously improved in the future to ensure the sustainability of the transportation industry. Meanwhile, the regression coefficients at the national level and in the eastern region were positive and significant at the levels of 10% and 5%, respectively, mainly because the per capita GDP in the eastern region is high and has promoted the improvement of the TFEE of the transportation industry. In the future, the cross-regional coordinated development of the transportation industry in the eastern region must be strengthened.

With regard to technological progress, which was among the control variables, the regression coefficients at the national level and in the eastern and central regions were negative but not significant, indicating that R&D investment has not promoted the convergence of TFEE in the transportation industry. The main reason is that the substantial differences in R&D input among the whole country, eastern region, and western region exert a minor convergence effect on the TFEE of the transportation industry. Thus, the R&D input must be reasonably adjusted in consideration of the foundation of the transportation industry in each province. The regression coefficient in the western region was positive and significant at the level of 1%, indicating that increasing R&D investment in the western region can further promote the convergence of TFEE in the transportation industry.

With regard to the opening degree, which was among the control variables, the regression coefficient at the national level and in the central region was negative but not significant. The regression coefficient in the western region was positive but not significant. The regression coefficient in the eastern region was positive and significant at the level of 10%. The higher the opening degree is, the faster the development of the tertiary industry is. Rapid development of the tertiary industry can promote and accelerate interregional transportation infrastructure network construction and facilitate the free flow of production factors in urban and rural areas. The eastern region, which has a good foundation of the tertiary industry, is characterized by the rapid development of the tertiary industry. It can meet individualized and multibatch transportation demands in small quantities in the tertiary industry on the basis of the good foundation of the transportation industry, thereby accelerating the TFEE convergence of the transportation industry in the eastern region.

With regard to population density, which was among the control variables, the regression coefficients throughout China and in the eastern, central, and western regions were positive, and those from the national level and the central region were significant at the levels of 1% and 5%, respectively. These results indicate that the TFEE convergence of the transportation industry can be accelerated by increasing the population density. A highly aggregated population can improve the land utilization rate and transportation efficiency, effectively reduce the average trip distance in cities, decrease unit transportation costs, realize the intensive development of the transportation industry, achieve fast cargo turnover and passenger transportation at the economic scale, and promote the improvement of the TFEE within this industry.

Conclusion

This study established a TFEE input–output evaluation system that considers carbon emission factors. The TFEE of China's transportation industry during 2004–2020 was quantitatively analyzed, and the convergent or divergent trend of TFEE was discussed through convergence analysis. The following conclusions were obtained.

(1) After the inclusion of carbon emission factors, the TFEE of China's transportation industry became 0.959, indicating specific pressure on the ecological environment. This efficiency value gradually declined from the eastern region to the central and western regions.

(2) The low TFEE of China's transportation industry was mainly ascribed to the inhibitory effect of technological changes. PEC, SEC, and TC reached 1.026, 1.013, and 0.951, respectively.

(3) At the national level, the TFEE of the transportation industry did not show any convergent trend. The interprovincial differences in energy efficiency are expected to exist for a long time, but the regions with low energy efficiency will catch up with those with high energy efficiency.

In this study, the unexpected output was the carbon emission of the transportation industry. However, the transportation industry has many unexpected output factors, including transportation safety accidents, traffic environment noise pollution, and direct loss of transportation. In follow-up research, such factors can be incorporated into models.

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